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ABSTRACT

This study investigated construct validity and factorial invariance of a performance assessment of reading comprehension and writing proficiency through a multitrait-multimethod (MTMM) structure using confirmatory factor analysis. The performance assessment was administered to 1,023 fifth and sixth graders. Interrater reliability was examined for each measured variable using three different generalizability coefficients. Although all of the measures were found to be highly reliable, exploratory factor analysis indicated that trait and method effects were confounded in the measured variables. Consequently, confirmatory factor analysis was used to disentangle multidimensionality and examine the convergent and discriminant validity of the latent variables according to the Campbell-Fiske criteria. A model with three correlated trait factors and three correlated method factors (MTMM structure) provided the best fit to the data. Factorial invariance across gender and grade was supported only for a particular set of parameters. Methodological and practical implications of the use of confirmatory factor analysis in MTMM analyses are also discussed for construct validation in performance assessment across different groups. (Contains 1 figure, 11 tables, and 36 references.) (Author/SLD)

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Application of Confirmatory Factor Analysis to the Validity Study of a Performance Assessment: A Multitrait-multimethod Structure and Its Invariance Across Gender and Grade

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Running head: PERFORMANCE ASSESSMENT

Performance assessment generally refers to a task (problem) that requires an individual to actively construct a response (solution), as opposed to simply recalling memorized knowledge (Baron, 1991). Although performance assessment has been quite popular in such areas as administration and management (Berk, 1986; Priestley, 1982), mechanical job performance appraisal (Priestley, 1982) and teacher evaluation (Stiggins & Bridgeford, 1984), it is only recently that performance assessment has been considered a viable approach to large scale testing of students' academic achievement (Kim, 1992).

If performance assessment is to be an acceptable alternative to traditional multiple-choice tests, it must be publicly accountable and professionally credible; that is, it must show sound technical adequacy with respect to reliability, validity, and scoring procedures (American Educational Research Association, American Psychological Association, and the National Council on Measurement in Education, 1985). Sometimes, however, these psychometric properties seem to be difficult to achieve with performance measures (Mehrens, 1992). An objective and reliable scoring of performance assessments requires careful and systematic training for examiners, which can be both time-consuming and expensive. Furthermore, performance assessments often have no evidence of validity other than face validity. Some degree of face validity may be essential for public acceptance, but this is not sufficient as the sole indicator of validity, particularly when the assessments are used in "high stakes" testing programs.

Questions concerning whether a test measures what it is intended to measure are answered through assessment of construct validity. Construct validity integrates a theoretical rationale with empirical evidence that bears on the interpretation or meaning of a measure (Messick, 1989). A construct, itself, can be defined as a product of informed scientific imagination—an idea developed to permit categorization and description of some directly observable behavior as representing an entity ("construct") that is not directly observable (Crocker & Algina, 1986). Traditionally, construct validation evidence is assembled through a series of studies including experimental, correlational, and discriminant approaches. When the adequacy of the test as an indicator of a construct is of primary concern, exploratory factor analysis and internal consistency assessment are typically conducted.

Compared to multiple-choice tests, the construct validation of performance assessments using constructed-response poses some additional problems. Regardless of the domain of assessment, language abilities, in particular, are likely to significantly influence scores[1], because most performance assessment requires students to demonstrate knowledge by actively constructing a written or oral response to a problem. Unless the assessment is designed solely to measure oral or written language skills, scores will be confounded. For example, students' written responses to open-ended mathematical problems will be influenced not only by their understanding of mathematics, but by their language fluency and writing abilities as well. More generally, "constructs" and "items" (questions) are likely to be confounded in performance assessment because multiple constructs are likely to be embedded in each item. Consequently, the relevant construct and the irrelevant method effects are entangled, and a unidimensional approach such as exploratory factor analysis fails to provide an adequate examination of construct validity; instead, a multidimensional analysis is required.

Along with these concerns, another potential threat to the validity of performance assessment is adverse impact on population subgroups. Because the response requires multiple traits, it is not easy to just measure the target component . One of the well-documented areas is a gender difference in performance assessment (Bennett, 1993). Several studies have found that relative to boys, girls perform better on constructed-response than on multiple-choice items. This gender-related format differences can be hypothesized that girls perform better because the constructed-response requires some construct-irrelevant attributes in which girls are strong (i.e., writing proficiency and verbal ability).

Research on gender difference in intellectual abilities has long been of interest to educators, which has found that girls tend to score higher than boys on tests of language usage (spelling, grammar) and perceptual speed (Feingold, 1992). Contemporary investigations have focused on two aspects: (a) difference in average performance through the meta-analytic review (Born, Bleichrodt, & Van Der Flier, 1987; Hyde & Linn, 1988) or the analysis of norms from standardized tests (Martin & Hoover, 1987) and (b) difference in variability in intellectual abilities (Feingold, 1992). In terms of psychometric studies on performance assessment, gender difference in mean levels of test scores is not necessarily a test bias. This difference may accurately represent essential distinction in group performance. Additionally, trend analyses have revealed that gender differences in intellectual abilities among adolescents have decreased markedly over the past generation (Feingold, 1988; Jacklin, 1989). As for performance assessment, the results of a recent state-wide alternative assessment system using constructed-response showed that boys seemed catch up with girls in junior high school level and score even better in high school level, even though girls did better in elementary level, in general (M. Davison, personal communication, April, 1994). Therefore, a more fundamental issue about construct validity is whether responses to the same test have the same meaning for boys and girls.

One classical approach to multidimensional analysis on construct validity is the multitrait-mulitimethod (MTMM) matrix developed by Campbell and Fiske (1959). With this technique, not only the constructs of interest but other dimensions of measurement (method effects) are also explicitly considered. An MTMM matrix is a matrix of correlations among measures of multiple traits, each of which is assessed by multiple methods. Although the MTMM matrix is the most widely used approach to evaluating multitrait-multimethod data, this approach has been criticized because it is based on the observed correlations between measured variables. A more advanced technique is the use of confirmatory factor analysis (CFA), inferring trait and method effects based on latent variables (Marsh, 1993; Marsh & Richards, 1985; Widaman, 1985; Wothke & Browne, 1990). The logic and heuristic value of the Campbell-Fiske criteria are still applicable; the difference is that they are applied to relationships among latent constructs, rather than measured variables (Marsh, 1989). Furthermore, by fixing or constraining various parameters, CFA can be used to test a variety of assumptions about the data (e.g., number of traits represented, whether traits are correlated) by specifying different models and empirically comparing how well these alternative models fit the data. This analytic approach thus provides a much stronger basis for analyzing multitrait-multimethod data.

The purpose of this study was to explore the utility of MTMM approaches to the investigation of the construct validity of performance assessments, using the particular example of an assessment of reading comprehension and writing ability. Assessment of these abilities using constructed response measures seemed particularly challenging. Conceptually, although both reading and writing are linguistic abilities, comprehension of a passage of text is somewhat distinct from the ability to communicate this understanding to others. In practice, however, scores for comprehension and writing ability based on the same sample of writing are almost certain to be confounded to some degree. Also, because scores from performance assessments of writing ability have been found to vary greatly as a function of topic (e.g., Breland, Camp, Jones, Morris, & Rock, 1987), method (question) effects are likely to be present in the data as well (i.e., scores for different traits assessed from responses to the same question may be correlated as highly as scores for the same trait assessed from the responses to different questions). Both of these factors should make it difficult to assess convergent and discriminant validity from correlations based on the measured variables. Once the MTMM structure was identified, testing for factorial invariance over different subpopulations was implemented. More specifically, we investigated whether this particular test have the same meaning for boys and girls of different grade levels.

Method

Subjects

Students participating in this research were part of a larger, longitudinal study of children's social, ethical, and intellectual development being conducted in six school districts-three in large cities, one in a small city and two in suburban communities. The districts are geographically diverse: three on the West Coast, one in the South, one in the Southeast, and one in the Northeast. Students from four elementary schools in each of the six districts took part in the study. The performance assessment was administered to 1,023 students (46% male, 54% female) in 5th or 6th grades (Grade 5 = 57%. Grade 6 = 43%) near the end of the school year (May).

Assessment Instrument and Procedures

The reading comprehension assessment used a 375-word passage from "The Little Prince" (de Saint-Exupery, 1943), with a Flesch grade level of 5.3. The passage describes the prince's encounter with a fox, during which the fox expresses the view that humans are only interested in hunting and raising chickens, and defines "tameness" as a unique bond between himself and a human being.

Students read the passage and then responded in writing to the following three questions about its meaning, under untimed conditions: (a) What did the fox mean about being tame? (b) Why does the fox want to be tame? (c) Why does the fox think men are only interested in hunting and raising chickens?

The scoring procedures were adapted from those used in the National Assessment of Educational Progress of reading and literature (National Assessment of Educational Progress, 1984), developed by the Educational Testing Service. Two trained raters scored students' written responses to the questions for *Understanding* (6 points), *Complexity of Writing* (5 points) , *Clarity of Thought* (4 points), and *Grammatical Usage and Spelling* (4 points). The scorers also counted the *Number of Words* written in response to each question. The final scale were created by averaging the two raters' scores. Because the first two questions both concerned students' understanding of the meaning of "tameness" in the passage, the first *Adequacy of Understanding* score was based on the written answers to both questions 1 and 2. All other measures were scored from the responses to each of the three questions. Thus, there were a total of 14 scores derived from each student's responses to the three questions. The detailed scoring guidelines are provided elsewhere (Developmental Studies Center, 1993).

Analysis

Interrater reliability was investigated through generalizability theory (Shavelson & Webb, 1991). To examine construct validity, an exploratory factor analysis using oblique rotation was first performed to examine preliminary factor structure. We then conducted confirmatory factor analysis of the latent constructs using EQS (Bentler, 1989). Finally, we examined factorial invariance across gender and grade through subsequent hierarchical nested models with various constraints.

Results

<u>Preliminary analyses</u>

Demonstrating that the measured variables are reliable is necessary before assessing construct validity. Because each variable was rated by two raters, of critical importance was the extent to which the scores of the two raters agreed (i.e., interrater agreement). Three generalizability (G) coefficients are reported in Table 1. The first G coefficient represents the extent to which raters rank ordered students in the same way (relative agreement). This is equivalent to the intraclass correlation coefficient. The second G coefficient, on the other hand, represents the extent to which students received identical scores from the two raters (absolute agreement). In terms of technical adequacy, absolute interrater agreement coefficients of .60 and higher are considered acceptable (Davison, 1989). Using this criterion, the level of absolute interrater agreement on every measured variable was good to excellent (.70 - .99). This finding confirms that a performance assessment can be reliable with careful rater-training and appropriate scoring criteria. Finally, the third G coefficient is the reliability when both raters' scores are combined (Coefficient Alpha), which is relevant in this investigation because we created the scale score by averaging two raters' scores. After all, all of the measured variables used in the analyses seemed to be very reliable (.83- .99).

Insert Table 1 About Here

Conceptually, the data should represent three traits: reading comprehension, *Writing Quality*, and *Writing Fluency*. An exploratory factor analysis of the 14 measured variables identified three factors, as shown in Table 2. However, the factor structure did not clearly reveal the expected three traits. Factor II does appear to represent *Writing Fluency*, with all six of the scores for *Number of Words* and *Complexity of Writing* having their highest loadings on this factor. In Factors I and III, however, method and trait effects are confounded. The scores for *Clarity of*

Thought, *Grammar (Grammatical Usage and Spelling)* and *Understanding* were clustered within different methods (questions) on these factors, with scores for questions 1 and 2 having their highest loadings on the first factor, and scores for question 3 having their highest loadings on the third.

Insert Table 2 About Here

Establishing an MTMM structure using Confirmatory Factor Analysis (CFA)

MTMM analysis produces factors corresponding to the traits and methods (questions). That is, factors defined by multiple indicators of the same trait reveal the construct validity of the trait, and factors identified by indicators derived from the same method represent method effects. MTMM analysis can be viewed as an application of confirmatory factor analysis with *á priori* factors assigned to traits and methods. An "anchor model" representing three (correlated) traits and three (correlated) method factors (corresponding to the three questions), as shown in Figure 1, was fit to the data.

Insert Figure 1 About Here

An advantage of MTMM studies using confirmatory factor analysis is that a series of alternative models can be tested against the anchor model. When the identified model is able to fit the data, various parameters in the model can be constrained to generate nested models, and these alternative models can be examined for their relative ability to fit the data. Several criteria were used to evaluate the adequacy of anchor model, and various alternative models, as shown in Table 3.

Insert Table 3 About Here

First, overall chi-square tests of goodness of fit, based on differences between the original and reproduced covariance matrices, are shown. This goodness of fit test, however, is dependent on sample size. Even a model which fits the data very well may produce a statistically significant chi-square for large sample sizes (Bollen & Long, 1993), as in the present case. To overcome this shortcoming, two alternative indices were considered.

Bentler and Bonett (1980) suggest that the goodness of fit of a particular model may be usefully assessed using the Comparative Fit Index which has the advantage of reflecting fit relatively well at all sample sizes. The second fit criterion has been derived on the basis of information theory considerations by Akaike (1989). In the spirit of parsimony, Akaike argued that when selecting a model from a large number of models, one should take into account both statistical goodness of fit and the number of parameters that have to be estimated to achieve that degree of fit. The Akaike Information Criterion (AIC) is designed to balance these two aspects of model fit. In general, small AICs result from models with few estimated parameters and a good fit to the data, whereas models with many parameters to be estimated yield large AICs.

Although the chi-square for the three trait, three method anchor model was statistically significant due to the large sample size, CFI indicated a good fit to the data, reaching .90 or higher (Bentler, 1989). Once this anchor model is established, alternative models can be fit to the data to test various hypotheses related to the Campbell-Fiske criteria (Campbell & Fiske, 1959). These alternative models can be compared for goodness of fit by taking the differences in their chi-square values and testing against the difference in the degrees of freedom (Bentler & Bonett, 1980). Various alternative models were assessed in the present study, and their fit indices are also summarized in Table 3.

Models 2 and 3 investigated the relative importance of method and trait factors. Model 2, including three method factors without traits, provided a poor fit to the data (CFI=.714). Model 3, containing three correlated trait factors without method factors, also showed a poor fit to the data (CFI=.653). These results indicate that both trait and method effects were necessary to adequately represent the data. The next two models therefore included both trait and method factors, but tested assumptions about the relationships among traits and methods. Both Model 4, in which the traits were assumed to be uncorrelated, and Model 5, in which the method factors were assumed to be uncorrelated, provided poor fits to the data (Model 4: CFI=.873; Model 5: CFI=.876). Thus, both correlated trait factors and correlated method factors were necessary assumptions.

We next examined the question of whether the correlations among the trait and method factors could be assumed to be equal. Model 6, with equal correlation of the method factors, seemed to fit the data almost as well as the anchor model (CFI=.898). However, the difference in chi-squares between the anchor model and Model 6 was highly significant. Model 7, representing equal correlation of the trait factors, provided a poor fit to the data (CFI=.873).

Finally, we examined whether a model with only two, rather than three traits, would adequately fit the data. Specifically, since the latent traits *Adequacy of Understanding* and *Writing Quality* seemed to be close each other in the exploratory factor analysis (see Table 2), the consequence of combining these two traits was examined. Although this two-trait, three methods factor model does not have a good conceptual justification, this model provides a test of the discriminant validity of the three trait factors. Model 8 had an acceptable fit to the data (CFI=.899), but, again, the difference in chi-squares between it and the anchor model was highly significant. In addition to the subsequent significant chi-square difference, the anchor model also had the smallest AIC value among the tested models, indicating that it was the most parsimonious model.

To summarize, the findings indicated:

1. The three trait factors were very important, showing good convergent validity, but a substantial portion of variance also depended on the method factors.

2. The three traits were significantly intercorrelated.

3. Elimination of any trait factors resulted in a significantly poorer fit. That is, discriminant validity was demonstrated in these analyses.

Invariance Constraints Across All Groups

The factor structure identified so far was based on data from the total sample of students. To examine the question of whether this structure would hold across four subgroups, the three trait, three method model was fit separately to data from boys and girls in grade 5 and 6. All four models showed an acceptable fit to the data. These results provide a support for the anchor model but do not explain the invariance of the parameter estimates across gender and grade. In order to test the appropriateness of the invariance, the hierarchical models for all four groups were also provided. The first model is the model in which no invariance constraints are imposed. This model provides a good baseline for comparing all subsequent models that impose invariance constraints hierarchically. According to the substantive interests and previous factorial invariance studies (e.g., Marsh, 1994), the hierarchical tests of the equality were conducted the following order: factor loadings for traits, factor loadings for methods, factor correlations for traits, factor correlations for methods, and residual variances.

Insert Table 4 About Here

Statistically significant change in chi-square, increment of the number of statistically significant constraints, CFI, and AIC indicated similar patterns. That is, lack of invariance was detected in factor loadings for traits and methods, and some parts of factor correlations (methods), and, especially, residual variances (significant chi-square change, large increment of the number of significant constraints, subsequently sharp decrease in CFI, and relatively large AIC). On the other hand, invariance of factor correlations for traits was rather supported. Because the hierarchical tests indicated lack of invariance in the set of parameters without pinpointing the particular estimate, it was necessary to examine the source of lack of invariance in the factor structure.

In Tables 5 to 8, detailed description of the factor structure was provided with parameter estimates in the starting model (no invariance constraints). There were also tests of equality constraints in each parameter so that we could identify any lack of invariance across four groups. In Table 5, trait factor loadings were reasonable and positive. Some part of equality constraints seemed to be inappropriate in *Writing Quality* and *Writing Fluency*. On the other hand, invariance of factor loadings of *Adequacy of Understudying* across four groups was supported. In method factor loadings, several estimates of each method showed lack of invariance across four groups (Table 6). In Table 7, the trait factor correlations between *Writing Quality* and *Writing Fluency* were problematic when the parameters were imposed to be invariant. As indicated above (see Table 4), there was a lack of invariance in all method factor correlations. Lastly, in Table 8, most components of the residual variances showed a lack of invariance.

Insert Tables 5 to 8 About Here

Invariance Across Grade Within Each Gender and Across Gender Within Each Grade

As Marsh (1994) showed the possibilities of testing the effects of gender, age, and interaction on the structure of academic self-concept, we tried to disentangle the similar effects on the MTMM structure in order to examine the factorial invariance as a function of gender, grade, and their joint effect. In Table 9, the first set of hierarchical models (grade 5 across gender) were the analyses to impose invariance over gender (boys and girls) in grade 5, and the second set of models (grade 6 across gender) impose invariance across gender in grade 6. In other words, invariance constraints over gender (boys and girls) were imposed in separate analyses of grade 5 and grade 6, and ,then, the chi-square and df from these separate analyses were summed for total models (the third set of models: across gender within grade). The results showed a similar pattern of lack of invariance (factor loadings and residual variances) in the previous four-group analyses (see Table 4). However, for sixth graders, invariance in method factor loadings and factor correlations (traits and methods) across gender seemed to be acceptable (insignificant chi-square change, stable CFI, and smaller AIC). This six-grade-model with both factor loadings and factor correlations invariant across gender was still able to fit to the data (CFI=.90). In the total models (across gender within grade), only trait- and method- factor correlations seemed to be invariant (insignificant chi-square change).

Insert Table 9 About Here

In table 10, we also imposed invariance constraints over grade levels in separate analyses of boys and girls, and then summed the chi-square and df from these separate analyses for total models (the third set of models: across grade within gender). For girls, invariance in method factor loadings and trait- and method-factor correlations could be properly imposed. In total models (across grade within gender), factor correlations (both trait and method) seemed to be invariant.

Insert Table 10 About Here

Summary of Effects of Grade, Gender, and Their Interaction on the MTMM Structure

The detailed analyses of various sets of hierarchical models indicated that only some portion of the MTMM structure was invariant across gender and grade. There was also a joint effect of gender and grade on invariance of MTMM structure. To sum up, the results suggested:

1. Trait facto: loadings showed a lack of invariance across gender and grade. The lack of fit was due to the inappropriateness of equality constraints across groups in the measured variables of *Writing Quality* and *Writing Fluency.*

2. Invariance of method factor loadings was influenced by joint effects of gender and grade. The invariance for sixth graders across gender, not for fifth graders, was supported. Also, the equality contra tints across grade for girls seemed to be appropriate, but not for boys.

3. Factor correlations for traits seemed to be invariant across gender and grade. Yet, invariance of factor correlations for methods were weakly supported.

4. There was a lack of invariance of residual variances due to gender and grade level.

The finding of a joint effect of gender and grade on the factorial invariance could be illustrated as the summary statistics[2] in Table 11. The first three columns in Table 11 come from the previous tables, such as total four-group (Table 4), total gender within grade (Table 9), and total grade within gender (Table 10). The χ^2 and df_d values in "Gender" column are the differences between values the first column (Four Groups) and the third column (Grade-Within-Gender). Likewise, the χ^2 and df_d values in "Grade" column are the differences between values the first column (Four Groups) and the second column (Gender-Within-Grade). Values pertinent to "interaction" were determined by substrating values in the fourth (Gender) and fifth (Grade) columns from the first column (Four Groups). According to this overview, there were simple main effects of gender and grade in tr ' factor loadings and method factor correlations. A joint effect of gender and grade was found in method factor loadings and residual variances.

Insert Table 11 About Here

General Discussion

This investigation examined the reliability and construct validity of a performance measure of reading comprehension and writing ability. The application of analytical scoring criteria to students' written responses to questions about their understanding of a passage of text by multiple raters yielded 14 scores that were found to be very reliable. Analysis of these scores revealed three trait factors which were significantly correlated (*Writing Quality*, *Writing Fluency*, and *Adequacy of Understanding*), as well as strong method (question) effects. Although significantly intercorrelated (particularly *Writing Quality* and *Adequacy of Understanding*), the three traits demonstrated both convergent and discriminant validity. This three-trait three-method model was found to fit the data for boys and girls, and for fifth and sixth grade students well, separately, although the factorial invariance across gender and grade was not fully supported.

Most interestingly, in the traits factors, factor correlations seemed to be stable while factor loadings showed a lack of invariance across gender, due not to *Adequacy of Understanding* but to the measured variables of writing components in the assessment (*Writing Quality* and *Writing Fluency*). This finding was somewhat corresponding to the notion of gender stereotypic model. That is, girls perform better on constructed-response because of some attributes in which girls are strong (i.e., writing proficiency). A detailed inspection of the estimates in the factor structure as a function of gender and grade is beyond the scope of this study and requires another systematic sample and defensible theoretical backgrounds. It, however, would be a worthy candidate for future research.

As shown previously, scores from performance assessments using constructed responses are likely to be question-specific or content-specific. In many cases, such as the present instance, a simple exploratory analysis is unable to disentangle the trait and method effects, and therefore cannot adequately reveal the complex structure of the data. MTMM analysis is an effective tool for investigating the construct validity of this sort of multidimensional measure. Through CFA, MTMM analysis has some advantages over the traditional MTMM matrix using correlations, such as (a) examining the relationship between important traits in school learning explicitly; (b) investigating the parameters as well as the measured variables; (c) evaluating alternative models in terms of constraining the relationships between variables; (d) removing method effects from estimates of traits.

In general, every measure can be considered to be a construct-method unit (Messick, 1993). Method variance includes all systematic effects associated with a particular measurement procedure that are extraneous to the focal construct being measured. The validity study, under MTMM analysis, is a systematic inquiry on construct-irrelevant variance and construct underreprsentation (Bennett, 1993; Messick, 1989). With an explicit construct network, one can differentiate the traits (construct-relevant variance) from the method effects (construct-irrelevant variance). The distinction between construct relevancy and irrelevancy is not absolute, but depends, to some degree, on the construct network in the particular context. The questions are considered construct-irrelevant (method) factors in the present example, but they could be considered part of a construct-relevant factor, if one assumed that the answer to a particular question required some unique instructionally relevant prior knowledge.

Throughout this investigation, we do recognize the exploratory nature of the analyses and also note several limitations of interpretations. First, there was a hierarchical structure in the data (Bryk & Raudenbush, 1992). Students were within the schools which belong to different districts. The multilevel covariance structure analysis cannot be implemented by the current stanadard programs such as LISREL or EQS so that these "design effects" were not properly specified. Second, a possibility of multiplicative models for the current MTMM structure was not explored (Cudeck, 1988), because, as asserted by Marsh (1995), we wanted to focus on the trait and method components associated with this hypothesized trait-method combination in performance assessment, and, ultimately, on the interpretation and improvement instruments.

This study is a preliminary step toward broadening and balancing the use of psychometric approaches in performance assessment. The scope of validity in any educational assessment extends to represent the meaningful construct network, and irrelevant effects are revealed more systematically. To maximize the utility of this dynamic approach to assessment, inclusive and complementary construct validation is needed. Research into ways of doing this will encompass psychometrics as well as substantial theoretical backgrounds in psychology and education.

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Footnotes

[1]Of course, reading ability influence scores on multiple-choice tests as well, but scores from performance assessments are influenced by expressive language abilities in addition to reading ability.

[2]Marsh (1994) provided an excellent description of a way to construct a summary statistics table. He also pointed out the potential problems and limitations of this approach.

Figure Caption

Figure 1. An anchor model (three correlated traits and three correlated methods) of MTMM structure using confirmatory factor analysis.

Table 1.

Interrater reliability: Generalizability Coefficients

Measured Variables	Variance Component (Student)	Variance Component (Rater)	Variance Component (Interaction)	Relative Error Variance	Absolute Error Variance	G1 (ICC): Relative Agreement	G2: Absolute Agreement	G3: (Alpha Coeff.)
Understanding (Q1 & Q2)	0.319	0.000	0.131	0.131	0.131	0.709	0.709	0.830
Understanding (Q3)	1.216	0.000	0.209	0.209	0.209	0.854	0.854	0.921
Q1 Complexity of Writing	1.018	0.000	0.197	0.197	0.197	0.838	0.838	0.912
Q1 Clarity of Thought	0.691	0.000	0.293	0.293	0.293	0.702	0.702	0.825
Q1 Grammar	0.539	0.000	0.208	0.208	0.208	0.722	0.721	0.838
Q2 Complexity of Writing	0.696	0.000	0.238	0.238	0.238	0.745	0.745	0.854
Q2 Clarity of Thought	0.531	0.002	0.216	0.216	0.218	0.711	0.709	0.831
Q2 Grammar	0.446	0.001	0.101	0.101	0.102	0.816	0.814	0.898
Q3 Complexity of Writing	0.746	0.006	0.248	0.248	0.254	0.750	0.746	0.857
Q3 Clarity of Thought	0.817	0.000	0.146	0.146	0.146	0.848	0.848	0.918
Q3 Grammar	0.575	0.001	0.110	0.110	0.111	0.840	0.838	0.913
Q1 No. of Words	119.022	0.000	0.029	0.029	0.029	0.999	0.999	0.999
Q2 No. of Words	69.608	0.000	0.947	0.947	0.947	0.987	0.987	0.993
Q3 No. of Words	53.349	0.001	0.132	0.132	0.132	0.998	0.998	0.999

Notes. G1 and G2 are reliability estimates of a randomly selected rating. G3 is a reliability estimate of two ratings combined.

Table 2

Exploratory Factor Analysis: Oblique Factor Model

Measured Variables	Factor I	Factor II	Factor III
Q1 Clarity of Thought	.802	-.085	.076
Q2 Clarity of Thought	.725	-.054	.116
Q1 Grammar	.558	.054	.141
Q2 Grammar	.300	.196	.285
Understanding (Q1 and Q2)	.690	.082	.070
Q2 No. of Words	.070	.807	-.019
Q2 Complexity of Writing	.089	.791	-.072
Q3 No. of Words	-.179	.771	.309
Q3 Complexity of Writing	-.219	.723	.314
Q1 No. of Words	.404	.642	-.197
Q1 Complexity of Writing	.491	.566	-.244
Q3 Clarity of Thought	.211	-.081	.802
Understanding (Q3)	.161	.028	.779
Q3 Grammar	.074	.219	.550

Factor pattern correlations

Factor I	1.000		
Factor II	.358	1.000	
Factor III	.252	.284	1.000

Eigen Values

	5.429	1.632	1.400

Table 3

Summary of Tested Models

Model descriptions	χ^2(df)	CFI	AIC	χ^2 diff (df)
1. Anchor Model-3 correlated trait-factors, 3 correlated method-factors	760.69 (56) **	.901	648.69	
2. Three correlated method-factors without trait-factors	2090.76 (73) **	.714	1944.76	1330.07 (17)**
3. Three correlated trait-factors without method-factors	2523.28 (74) **	.653	2375.28	1762.59 (18)**
4. Three UNcorrelated trait-factors and three correlated method-factors	958.23 (59) **	.873	840.23	197.54 (3)**
5. Three correlated trait-factors and three UNcorrelated method-factors	935.16 (59) **	.876	817.16	174.47 (3)**
6. Anchor Model with equal correlations among method-factors	780.20 (58) **	.898	664.19	19.51 (2)**
7. Anchor Model with equal correlations among trait-factors	958.23 (59) **	.873	840.23	197.54 (3)**
8. Two correlated trait-factors (Understanding and Writing Quality combined) and three correlated method-factors	772.04 (58) **	.899	656.04	11.35 (2)*

Notes. CFI (Comparative Fit Index) is based on a Null Model with χ^2(df)=7149.95 (91). The χ^2 difference is based on the difference between the Anchor Model (Model 1) and the model being tested.

* $p< 0.01$.

** $p< 0.001$.

Table 4

Summary of Goodness of Fit for Each Group with No Constraints and All Groups with Hierarchical Constraints

Model	AIC	χ^2	df	CFI	χ^2_d	df_d	Δ of Sig. Constraints
No Eqaulity Constraints							
Grade 5/Female	141.58	253.58	56	.905			
Grade 5/Male	107.31	219.32	56	.905			
Grade 6/Female	109.81	221.81	56	.899			
Grade 6/Male	46.69	158.69	56	.913			
Total (Across Four Groups)							
No Equality Constraints	405.16	853.36	224	.905			
Constraints FL (T)	479.56	1011.56	266	.887	158.20*	42	8
Constraints FL (T,M)	478.02	1100.02	311	.881	88.46*	45	9
Constraints FL (T,M), FC (T)	471.23	1111.23	320	.881	11.21	9	1
Constraints FL (T,M), FC (T,M)	472.25	1130.25	329	.879	19.02+	9	4
Constraints FL, FC, R	525.74	1267.74	371	.865	137.49*	42	14

Notes. FL=factor loadings, FC=factor correlation, R=Residual, T=Trait, M=Method; AIC=Akaike Information Criterion; CFI=Comparative Fit Index; χ^2_d and df_d indicate subsequent difference in χ^2 and df from less constraints to more constraints in the model; The χ^2(df=91) for the null models are 2173.50 (Grade 5/Female), 1802.15 (Grade 5/Male), 1735.70 (Grade 6/Female), and 1277.85 (Grade 6/Male); Δ of Sig. Constraints refers to increment of the number of statistically significant constraints ($p<.05$, univarite Lagrange Multiplier test), when moving toward a more restrictive model.

+ $p<.05$. * $p<.01$.

Table 5

Estimates for the Model with Three Traits and Three Methods with No Constraints: Trait Factor Loadings

Trait	Measured Variables	Grade 5-Female	Grade 5-Male	Grade 6-Female	Grade 6-Male
		Factor Loadings for Traits (Unstandardized/Standardized)			
Trait 1	Understanding (Q1 & Q2)	.209/.341	.195/.402	.318/.523	.218/.437
(Adequancy of Understanding)	Understanding (Q3)	.722/.756	.898/.943	.523/527	.413/.420
Trait 2	Q1 Clarity[a]	.315/392	.349/.443	.420/.579	.270/.371
(Writing Quality)	Q2 Clarity[a]	.204/.331	.277/.405	.296/.531	.262/.452
	Q3 Clarity[a]	.537/.771	.619/.880	.386/.596	.300/.444
	Q1 Grammar	.141/.221	.311/.412	.339/.525	.376/.529
	Q2 Grammar[a]	.066/.119	.206/.342	.274/.494	.435/.739
	Q3 Grammar[a]	.108/.194	.272/.476	.324/.580	.409/.723
Trait 3	Q1 Complexity	.385/.404	.454/.513	.512/.536	.437/.480
(Writing Fluency)	Q2 Complexity[a]	.719/.753	.523/.723	.589/.587	.344/.432
	Q3 Complexity[a]	.280/.299	.314/.422	.788/.793	.645/.734
	Q1 No. of Words	.335/.410	.441/.615	.491/.553	.421/.550
	Q2 No. of Words[a]	.525/.637	.482/.747	.488/.578	.397/.560
	Q3 No. of Words	.211/.276	.313/.541	.759/.934	.569/.881

[a]When the parameters in the structure were imposed to be invariant across 4 groups (6 constraints), at least one set of equality constraints seemed to be inappropriate, according to the univariate Lagrange Multiplier test ($p<.05$).

Table 6

Estimates for the Model with Three Traits and Three Methods with No Constraints: Method Factor Loadings

		Factor Loadings for Methods (Unstandardized/Standardized)			
Method	Measured Variables	Grade 5-Female	Grade 5-Male	Grade 6-Female	Grade 6-Male
Method 1	Understanding (Q1 and Q2)[a]	.146/.238	.045/.093	.104/.172	.153/.307
(Question 1)	Q1 Clarity	.434/.540	.453/.575	.268/.369	.297/.407
	Q1 Grammar	.314/.472	.222/.293	.174/.270	.118/.166
	Q1 Complexity	.752/.789	.628/.708	.764/.800	.742/.814
	Q1 No. of Words[a]	.628/.770	.459/.640	.594/.669	.452/.591
Method 2	Understanding (Q1 and Q2)[a]	.267/.435	.322/.664	.147/.242	.054/.109
(Question 2)	Q2 Clarity[a]	.320/.518	.466/.682	.168/.301	.066/.113
	Q2 Grammar[a]	.334/.602	.198/.329	.099/.179	.019/.033
	Q2 Complexity	.511/.535	.307/.424	.654/.652	.720/.902
	Q2 No. of Words	.496/.601	.311/.482	.580/.688	.392/.553
Method 3	Understanding (Q3)	.329/.344	.011/.012	.817/.824	.812/.827
(Question 3)	Q3 Clarity	.186/.268	-.057/-.080	.368/.569	.467/.691
	Q3 Grammar	.222/.400	.101/.177	.074/.133	.021/.037
	Q3 Complexity	.689/.735	.481/.647	.262/.264	.204/.232
	Q3 No. of Words[a]	.689/.901	.453/.784	.084/.104	.111/.165

[a]When the parameters in the structure were imposed to be invariant across 4 groups (6 constraints), at least one set of equality constraints seemed to be inappropriate, according to the univariate Lagrange Multiplier test ($p<.05$).

Table 7.

Estimates for the Model with Three Traits and Three Methods with No Constraints: Factor Correlations

	Grade 5-Female	Grade 5-Male	Grade 6-Female	Grade 6-Male
Correlations Between Traits				
Understanding and Writing Quality	.999	.862	.971	.896
Understanding and Writing Fluency	.459	.369	.471	.590
Writing Quality and Writing Fluency[a]	.292	.379	.479	.522
Correlations Between Methods				
Question 1 and Question 2[a]	.475	.555	.344	.165
Question 1 and Question 3[a]	.312	.215	.096	.018
Question 2 and Question 3[a]	.479	.326	.019	.087

[a]When the parameters in the structure were imposed to be invariant across 4 groups (6 constraints), at least one set of equality constraints seemed to be inappropriate, according to the univariate Lagrange Multiplier test ($p<.05$).

Table 8

Estimates for the Model with Three Traits and Three Methods with No Constraints: Residual Variance

	Residual Variance (Unstandardized/Standardized)			
Measured Variables	Grade 5-Female	Grade 5-Male	Grade 6-Female	Grade 6-Male
Understanding(Q1 & Q2)[a]	.203/.735	.075/.566	.225/.781	.173/.832
Understanding (Q3)	.283/.557	.100/.332	.043/.209	.136/.375
Q1 Clarity	.357/.745	.295/.688	.279/.727	.370/.835
Q2 Clarity[a]	.237/.789	.173/.609	.195/.792	.264/.885
Q3 Clarity[a]	.161/.577	.108/.468	.134/.566	.148/.570
Q1 Grammar[a]	.325/.856	.425/.863	.271/.807	.350/.832
Q2 Grammar	.192/.789	.281/.880	.222/.851	.157/.673
Q3 Grammar	.247/.896	.242/.861	.202/.804	.153/.690
Q1 Complexity[a]	.195/.463	.186/.486	.067/.271	.089/.327
Q2 Complexity[a]	.134/.383	.156/.546	.231/.479	.000/.000
Q3 Complexity[a]	.327/.609	.223/.635	.298/.549	.314/.638
Q1 No. of Words[a]	.158/.488	.109/.460	.195/.497	.205/.591
Q2 No. of Words[a]	.159/.483	.087/.458	.137/.439	.191/.617
Q3 No. of Words[a]	.066/.335	.031/.303	.078/.343	.090/.443

[a]When the parameters in the structure were imposed to be invariant across 4 groups (6 constraints), at least one set of equality constraints seemed to be inappropriate, according to the univariate Lagrange Multiplier test ($p<.05$).

Table 9

Summary of Goodness of Fit for Invariance Constraints Across Gender within Grade

Model	AIC	χ^2	df	CFI	χ^2_d	df_d	Δ of Sig. Constraints
Grade 5 Across Gender							
No Equality Constraints	248.97	472.87	112	0.905			
Constraints FL (T)	253.84	505.84	126	0.900	32.97*	14	3
Constraints FL (T,M)	278.25	560.25	141	0.889	54.41*	15	5
Constraints FL (T,M), FC (T)	277.23	565.23	144	0.889	4.98	3	0
Constraints FL (T,M), FC (T,M)	279.37	573.37	147	0.888	8.14+	3	2
Constraints FL, FC, R	334.05	656.05	161	0.870	82.68*	14	7
Grade 6 Across Gender							
No Equality Constraints	156.49	380.49	112	0.905			
Constraints FL (T)	154.38	406.38	126	0.901	25.89+	14	1
Constraints FL (T,M)	141.88	423.88	141	0.900	17.50	15	1
Constraints FL (T,M), FC (T)	139.54	427.54	144	0.900	3.66	3	0
Constraints FL (T,M), FC (T,M)	135.80	429.80	147	0.900	2.26	3	0
Constraints FL, FC, R	131.96	453.96	161	0.897	24.16+	14	2
Total (Gender-Within-Grade)							
No Equality Constraints		853.36	224				
Constraints FL (T)		912.22	252		58.86*	28	
Constraints FL (T,M)		984.13	282		71.91*	30	
Constraints FL (T,M), FC (T)		992.77	288		8.64	6	
Constraints FL (T,M), FC (T, M)		1003.17	294		10.40	6	
Constraints FL, FC, R		1110.01	322		106.84*	28	

Notes. FL=factor loadings, FC=factor correlation, R=Residual, T=Trait, M=Method; AIC=Akaike Information Criterion; CFI=Comparative Fit Index; χ^2_d and df_d indicate subsequent difference in χ^2 and df from less constraints to more constraints in the model.

+ $p<.05$. * $p<.01$.

Table 10

Summary of Goodness of Fit for Invariance Constraints Across Grade within Gender

Model	AIC	χ^2	df	CFI	χ^2_d	df_d	Δ of Sig. Constraints
Female Across Grade							
No Equality Constraints	251.36	475.36	112	.903			
Constraints FL (T)	251.46	503.46	126	.899	28.10+	14	1
Constraints FL (T,M)	233.64	515.64	141	.899	12.18	15	0
Constraints FL (T,M), FC (T)	234.99	522.99	144	.898	7.35	3	1
Constraints FL (T,M), FC (T,M)	234.01	528.01	147	.898	5.02	3	1
Constraints FL, FC, R	231.93	553.93	161	.895	25.92+	14	1
Male Across Grade							
No Equality Constraints	154.01	378.00	112	.908			
Constraints FL (T)	217.73	469.73	126	.881	91.73*	14	2
Constraints FL (T,M)	222.73	504.73	141	.874	35.00*	15	3
Constraints FL (T,M), FC (T)	218.48	506.48	144	.875	1.75	3	0
Constraints FL (T,M), FC (T,M)	216.99	510.99	147	.874	4.51	3	0
Constraints FL, FC, R	233.97	555.97	161	.864	44.98*	14	6
Total (Grade-Within-Gender)							
No Equality Constraints		853.36	224				
Constraints FL (T)		973.19	252		119.83*	28	
Constraints FL (T,M)		1020.37	282		47.18+	30	
Constraints FL (T,M), FC (T)		1029.47	288		9.10	6	
Constraints FL (T,M), FC (T, M)		1039.00	294		9.53	6	
Constraints FL, FC, R		1109.90	322		70.90*	28	

Notes. FL=factor loadings, FC=factor correlation, R=Residual, T=Trait, M=Method; AIC=Akaike Information Criterion; CFI=Comparative Fit Index; χ^2_d and df_d indicate subsequent difference in χ^2 and df from less constraints to more constraints in the model.

+ $p<.05$. * $p<.01$.

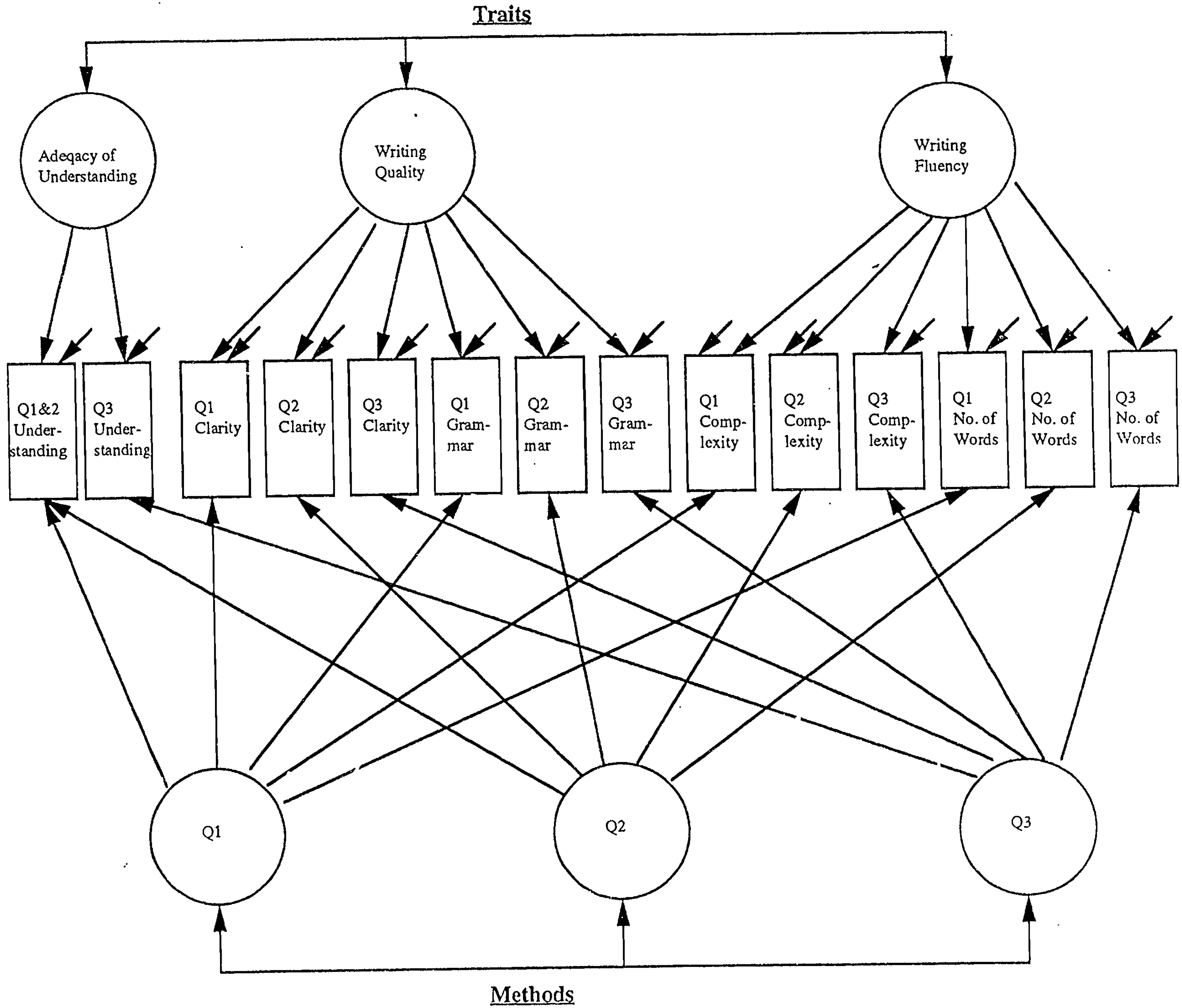
Table 11

Estimates of Gender, Grade, and Interaction Effects to the Multitrait-multimethod Structure

Parameter Constraints		Four Groups	Gender-Within-Grade	Grade-Within-Gender	Gender	Grade	Interaction Equivalent
FL (T)	χ^2_d	158.20*	58.86*	119.83*	38.37*	99.34*	20.49
	df_d	42	28	28	14	14	14
FL (M)	χ^2_d	88.46*	71.91*	47.18+	41.28*	16.55	30.63*
	df_d	45	30	30	15	15	15
FC (T)	χ^2_d	11.21	8.64	9.10	2.11	2.57	6.53
	df_d	9	6	6	3	3	3
FC (M)	χ^2_d	19.02+	10.40	9.53	9.49+	8.62+	0.91
	df_d	9	6	6	3	3	3
R	χ^2_d	137.49*	106.84*	70.90*	66.59*	30.65*	40.25*
	df_d	42	28	28	14	14	14

Notes. FL=factor loadings, FC=factor correlation, R=Residual, T=Trait, M=Method; χ^2_d and df_d indicate subsequent difference in χ^2 and df from less constraints to more constraints in the model.

+ $p<.05$. * $p<.01$.



Traits
Adeqacy of Understanding
Writing Quality
Writing Fluency
Q1&2 Under-standing
Q3 Under-standing
Q1 Clarity
Q2 Clarity
Q3 Clarity
Q1 Gram-mar
Q2 Gram-mar
Q3 Gram-mar
Q1 Comp-lexity
Q2 Comp-lexity
Q3 Comp-lexity
Q1 No. of Words
Q2 No. of Words
Q3 No. of Words
Q1
Q2
Q3
Methods

Abstract

This study investigated construct validity and factorial invariance of a performance assessment of reading comprehension and writing proficiency, through a multitrait-multimethod structure, using confirmatory factor analysis technique. First, interrater reliability was examined for each measured variable using three different generalizability coefficients. Although all of the measures were found to be highly reliable, exploratory factor analysis indicated that trait and method effects were confounded in the measured variables. Consequently, confirmatory factor analysis was used to disentangle multidimensionality and examine the convergent and discriminant validity of the latent variables according to the Campbell-Fiske criteria. These analyses indicated that a model with three correlated trait factors and three correlated method factors (MTMM structure) provided the best fit to the data. Finally, a factorial invariance across gender and grade was examined. While this MTMM factor structure was fitted to the data in each subgroup (fifth grade boys, fifth grade girls, sixth grade boys, and sixth grade girls), the factorial invariance across gender and grade was supported only in a particular set of parameters. Methodological and practical implications of the use of confirmatory factor analysis in multitrait-multimethod analyses are also discussed for construct validation in performance assessment across different groups .